VinBigData Chest X-ray classification-model

April 28, 2021

1 Data processing

[1]:
```
!nvidia-smi
```

```
Thu Apr 22 18:56:43 2021
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 450.51.06    Driver Version: 450.51.06    CUDA Version: 11.0     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  Tesla P100-PCIE…  Off  | 00000000:00:04.0 Off |                    0 |
| N/A   40C    P0    28W / 250W |      0MiB / 16280MiB |      0%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|  No running processes found                                                 |
+-----------------------------------------------------------------------------+
```

[2]:
```
# Download efficientnets
!pip install keras_efficientnets
```

```
Collecting keras_efficientnets
  Downloading keras_efficientnets-0.1.7-py2.py3-none-any.whl (15 kB)
Requirement already satisfied: keras>=2.2.4 in /opt/conda/lib/python3.7/site-
packages (from keras_efficientnets) (2.4.3)
Requirement already satisfied: scikit-learn>=0.21.2 in
/opt/conda/lib/python3.7/site-packages (from keras_efficientnets) (0.24.1)
Requirement already satisfied: scipy>=1.1.0 in /opt/conda/lib/python3.7/site-
packages (from keras_efficientnets) (1.5.4)
Requirement already satisfied: h5py in /opt/conda/lib/python3.7/site-packages
(from keras>=2.2.4->keras_efficientnets) (2.10.0)
```

```
Requirement already satisfied: numpy>=1.9.1 in /opt/conda/lib/python3.7/site-
packages (from keras>=2.2.4->keras_efficientnets) (1.19.5)
Requirement already satisfied: pyyaml in /opt/conda/lib/python3.7/site-packages
(from keras>=2.2.4->keras_efficientnets) (5.3.1)
Requirement already satisfied: joblib>=0.11 in /opt/conda/lib/python3.7/site-
packages (from scikit-learn>=0.21.2->keras_efficientnets) (1.0.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/opt/conda/lib/python3.7/site-packages (from scikit-
learn>=0.21.2->keras_efficientnets) (2.1.0)
Requirement already satisfied: six in /opt/conda/lib/python3.7/site-packages
(from h5py->keras>=2.2.4->keras_efficientnets) (1.15.0)
Installing collected packages: keras-efficientnets
Successfully installed keras-efficientnets-0.1.7
```

[3]:

```
#Keras Applications is the applications module of the Keras deep learning␣
↪library. It provides model definitions and pre-trained weights for a number␣
↪of popular archictures, such as VGG16, ResNet50, Xception, MobileNet, and␣
↪more.
!pip install Keras-Applications
```

```
Collecting Keras-Applications
  Downloading Keras_Applications-1.0.8-py3-none-any.whl (50 kB)
     |                  | 50 kB 272 kB/s
Requirement already satisfied: h5py in /opt/conda/lib/python3.7/site-
packages (from Keras-Applications) (2.10.0)
Requirement already satisfied: numpy>=1.9.1 in /opt/conda/lib/python3.7/site-
packages (from Keras-Applications) (1.19.5)
Requirement already satisfied: six in /opt/conda/lib/python3.7/site-packages
(from h5py->Keras-Applications) (1.15.0)
Installing collected packages: Keras-Applications
Successfully installed Keras-Applications-1.0.8
```

[4]:

```
#importing other required libraries
import numpy as np
import pandas as pd
from sklearn.utils.multiclass import unique_labels
import os
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import seaborn as sns
import itertools
from tqdm import tqdm
import shutil
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix

#Onehot Encoding the labels.
```

```
from sklearn.utils.multiclass import unique_labels
import albumentations
from sklearn.metrics import classification_report, confusion_matrix



# tensoflow models
import tensorflow as tf
from keras import Sequential
from tensorflow import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Conv2D, MaxPooling2D
from tensorflow.keras.layers import Dense, Dropout, Flatten, Activation
from tensorflow.keras.models import Sequential
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau,␣
↪ModelCheckpoint
from tensorflow.keras.optimizers import Adam
from keras_efficientnets import EfficientNetB0
from keras.utils import to_categorical
```

[5]:
```
# creat folder
os.makedirs("./self_cas_study", exist_ok=True)
```

[6]:
```
# the train set metadata, with one row for each object, including a class and a␣
↪bounding box.
df_train = pd.read_csv('../input/vinbigdata-chest-xray-abnormalities-detection/
↪train.csv')
print(df_train.shape)
df_train.head()
```

```
(67914, 8)
```

[6]:
```
                           image_id          class_name  class_id rad_id  \
0  50a418190bc3fb1ef1633bf9678929b3          No finding        14    R11
1  21a10246a5ec7af151081d0cd6d65dc9          No finding        14     R7
2  9a5094b2563a1ef3ff50dc5c7ff71345        Cardiomegaly         3    R10
3  051132a778e61a86eb147c7c6f564dfe  Aortic enlargement         0    R10
4  063319de25ce7edb9b1c6b8881290140          No finding        14    R10

    x_min   y_min   x_max   y_max
0     NaN     NaN     NaN     NaN
1     NaN     NaN     NaN     NaN
2   691.0  1375.0  1653.0  1831.0
3  1264.0   743.0  1611.0  1019.0
4     NaN     NaN     NaN     NaN
```

In EDA we created files which stores the 15000 images and its respective class. Images is lables as

'1' if No lung diseases find in image and '0' if images aslung diseases

[7]:
```
#load classfication.csv file
df = pd.read_csv('../input/personil/classfication.csv')
print(df.shape)
df.head()
```

```
(15000, 2)
```

[7]:

	target	img_path
0	1	../input/vinbigdata/train/000434271f63a053c412…
1	1	../input/vinbigdata/train/00053190460d56c53cc3…
2	0	../input/vinbigdata/train/0005e8e3701dfb1dd93d…
3	1	../input/vinbigdata/train/0006e0a85696f6bb578e…
4	0	../input/vinbigdata/train/0007d316f756b3fa0bae…

This model takes input images of shape (224, 224, 3)

[8]:
```
# Specify image size
IMG_WIDTH = 224
IMG_HEIGHT = 224
CHANNELS = 3
```

[9]:
```
# load the test samples
test_df = pd.read_csv('../input/vinbigdata-chest-xray-abnormalities-detection/
↪sample_submission.csv')
```

[10]:
```
# add .png to images id
def append_ext(fn):
  return fn+".png"
test_df["img_id"]=test_df["image_id"].apply(append_ext)
```

[11]:
```
test_df.head()
```

[11]:

	image_id	PredictionString	\
0	002a34c58c5b758217ed1f584ccbcfe9	14 1 0 0 1 1	
1	004f33259ee4aef671c2b95d54e4be68	14 1 0 0 1 1	
2	008bdde2af2462e86fd373a445d0f4cd	14 1 0 0 1 1	
3	009bc039326338823ca3aa84381f17f1	14 1 0 0 1 1	
4	00a2145de1886cb9eb88869c85d74080	14 1 0 0 1 1	

	img_id
0	002a34c58c5b758217ed1f584ccbcfe9.png
1	004f33259ee4aef671c2b95d54e4be68.png
2	008bdde2af2462e86fd373a445d0f4cd.png
3	009bc039326338823ca3aa84381f17f1.png
4	00a2145de1886cb9eb88869c85d74080.png

[12]:
```
# adding .png to image index
df['img_id']= df.img_path.str.split('/',expand=True)[4]
```

[13]:
```
#x_train,x_val= train_test_split(df,test_size=0.25,shuffle=True,stratify=df.
↪target)
```

[14]:
```
#Verifying the dimension after one hot encoding
#print(x_train.shape)
#print(x_val.shape)
```

[15]:
```
'''DATA_PATH = '/content/drive/MyDrive/self case study 2/train'
output_path= '/content/drive/MyDrive/self case study 2/'
def process_data(data,data_type='train_img'):
  for _,row in tqdm(data.iterrows(),total=len(data)):
    image_name= row['img_id']
    shutil.copyfile(os.path.join(DATA_PATH,image_name),os.path.
↪join(output_path,f'{data_type}/{image_name}'))'''
```

[15]:
```
"DATA_PATH = '/content/drive/MyDrive/self case study 2/train'\noutput_path=
'/content/drive/MyDrive/self case study 2/'\ndef
process_data(data,data_type='train_img'):\n  for _,row in
tqdm(data.iterrows(),total=len(data)):\n    image_name= row['img_id']\n    shuti
l.copyfile(os.path.join(DATA_PATH,image_name),os.path.join(output_path,f'{data_t
ype}/{image_name}'))"
```

[16]:
```
#process_data(x_train,data_type='train_img')
#process_data(x_val,data_type='val_img')
```

Image augmentation

[17]:
```
# we are applying data image augmentation
datagen= ImageDataGenerator(rotation_range=20,
                                   width_shift_range=0.2,
                                   height_shift_range=0.2,
                                   zoom_range=0.2,
                                   featurewise_center=True,
                                   featurewise_std_normalization=True,
                                   brightness_range=[0.3,0.6],
                                   horizontal_flip=True,
                                   vertical_flip=False,
                                   fill_mode="wrap",rescale=1/255.,␣
↪validation_split=0.2)
```

[18]:
```
train_generator = datagen.flow_from_dataframe(dataframe=df, directory='../input/
↪vinbigdata/train',
                                             x_col='img_id',
                                             y_col='target',
```

```
                                                          class_mode='raw',
                                                          target_size=(IMG_WIDTH,␣
 ↪IMG_HEIGHT),
                                                          batch_size=64,
                                                         ␣
 ↪subset='training',seed=42,shuffle=True)
validation_generator = datagen.flow_from_dataframe(dataframe=df, directory='../
 ↪input/vinbigdata/train',
                                                          x_col='img_id',
                                                          y_col='target',
                                                          class_mode='raw',
                                                          target_size=(IMG_WIDTH,␣
 ↪IMG_HEIGHT),
                                                          batch_size=64,
                                                         ␣
 ↪subset='validation',seed=42,shuffle=False)
```

```
Found 12000 validated image filenames.
Found 3000 validated image filenames.
```

[19]:
```
# create pipleline on test data
test_datagen = ImageDataGenerator(rescale=1/255)
test_generator=test_datagen.flow_from_dataframe(dataframe=test_df,directory="../
 ↪input/vinbigdata/test",
                                                       x_col="img_id",
                                                       y_col=None,
                                                       batch_size=1,seed=42,shuffle=False,
                                                       target_size=(IMG_WIDTH, IMG_HEIGHT),
                                                       class_mode=None)
```

```
Found 3000 validated image filenames.
```

2 Training a model from scratch

[20]:
```
NUM_CLASSES = 2
#Defining the model
model= Sequential()
base_model = EfficientNetB0(include_top=False, weights="imagenet",␣
 ↪input_shape=(IMG_WIDTH, IMG_HEIGHT, 3),classes=NUM_CLASSES)
model.add(base_model)
model.add(Flatten())
model.add(Dense(256,activation=('relu')))
model.add(Dropout(.3))
model.add(Dense(128,activation=('relu')))
model.add(Dropout(.2))
model.add(Dense(2,activation=('softmax')))
```

```
#Model summary
model.summary()
```

```
Downloading data from https://github.com/titu1994/keras-
efficientnets/releases/download/v0.1/efficientnet-b0_notop.h5
16719872/16717576 [==============================] - 1s 0us/step
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
model (Functional)           (None, 7, 7, 1280)        4049564
_________________________________________________________________
flatten (Flatten)            (None, 62720)             0
_________________________________________________________________
dense (Dense)                (None, 256)               16056576
_________________________________________________________________
dropout (Dropout)            (None, 256)               0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               32896
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_2 (Dense)              (None, 2)                 258
=================================================================
Total params: 20,139,294
Trainable params: 20,097,278
Non-trainable params: 42,016
_________________________________________________________________
```

[21]:
```
#Defining the parameters
batch_size= 100
#learn_rate=.001
#sgd=SGD(lr=learn_rate,momentum=.9,nesterov=False)
model.compile(optimizer="adam", loss="sparse_categorical_crossentropy",␣
↪metrics=["acc"])
```

[22]:
```
train_steps = train_generator.n//train_generator.batch_size
validation_steps = validation_generator.n//validation_generator.batch_size
```

[23]:
```
os.makedirs("self_cas_study/models", exist_ok=True)
train_steps = train_generator.n//train_generator.batch_size
validation_steps = validation_generator.n//validation_generator.batch_size

# check points
checkpointer = ModelCheckpoint('self_cas_study/models/best_model.
↪h5',monitor='val_acc',verbose=1,save_best_only=True,save_weights_only=True)
```

```
history = model.fit(train_generator,steps_per_epoch=train_steps,verbose␣
↪=2,epochs=20,validation_data=validation_generator,validation_steps=validation_steps,callbac
↪= [checkpointer])
```

```
/opt/conda/lib/python3.7/site-
packages/keras_preprocessing/image/image_data_generator.py:720: UserWarning:
This ImageDataGenerator specifies `featurewise_center`, but it hasn't been fit
on any training data. Fit it first by calling `.fit(numpy_data)`.
  warnings.warn('This ImageDataGenerator specifies '
/opt/conda/lib/python3.7/site-
packages/keras_preprocessing/image/image_data_generator.py:728: UserWarning:
This ImageDataGenerator specifies `featurewise_std_normalization`, but it hasn't
been fit on any training data. Fit it first by calling `.fit(numpy_data)`.
  warnings.warn('This ImageDataGenerator specifies '
```

```
Epoch 1/20
187/187 - 400s - loss: 0.4898 - acc: 0.8265 - val_loss: 7.5468 - val_acc: 0.7092

Epoch 00001: val_acc improved from -inf to 0.70924, saving model to
self_cas_study/models/best_model.h5
Epoch 2/20
187/187 - 269s - loss: 0.2654 - acc: 0.8923 - val_loss: 0.4969 - val_acc: 0.8662

Epoch 00002: val_acc improved from 0.70924 to 0.86617, saving model to
self_cas_study/models/best_model.h5
Epoch 3/20
187/187 - 269s - loss: 0.2252 - acc: 0.9083 - val_loss: 0.2652 - val_acc: 0.8835

Epoch 00003: val_acc improved from 0.86617 to 0.88349, saving model to
self_cas_study/models/best_model.h5
Epoch 4/20
187/187 - 268s - loss: 0.2152 - acc: 0.9163 - val_loss: 0.2897 - val_acc: 0.8723

Epoch 00004: val_acc did not improve from 0.88349
Epoch 5/20
187/187 - 267s - loss: 0.2085 - acc: 0.9196 - val_loss: 0.2043 - val_acc: 0.9151

Epoch 00005: val_acc improved from 0.88349 to 0.91508, saving model to
self_cas_study/models/best_model.h5
Epoch 6/20
187/187 - 267s - loss: 0.1902 - acc: 0.9270 - val_loss: 0.3592 - val_acc: 0.8580

Epoch 00006: val_acc did not improve from 0.91508
Epoch 7/20
187/187 - 267s - loss: 0.1857 - acc: 0.9252 - val_loss: 0.2021 - val_acc: 0.9239

Epoch 00007: val_acc improved from 0.91508 to 0.92391, saving model to
```

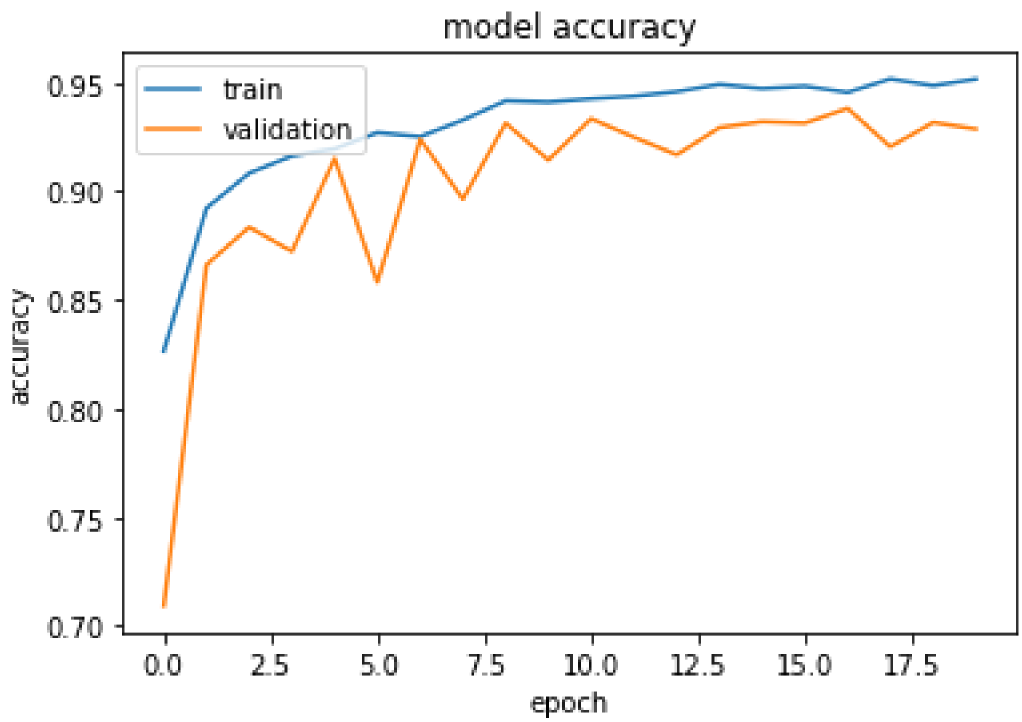
```
self_cas_study/models/best_model.h5
Epoch 8/20
187/187 - 265s - loss: 0.1659 - acc: 0.9328 - val_loss: 0.2498 - val_acc: 0.8964

Epoch 00008: val_acc did not improve from 0.92391
Epoch 9/20
187/187 - 267s - loss: 0.1506 - acc: 0.9417 - val_loss: 0.1625 - val_acc: 0.9314

Epoch 00009: val_acc improved from 0.92391 to 0.93139, saving model to
self_cas_study/models/best_model.h5
Epoch 10/20
187/187 - 266s - loss: 0.1517 - acc: 0.9411 - val_loss: 0.2234 - val_acc: 0.9144

Epoch 00010: val_acc did not improve from 0.93139
Epoch 11/20
187/187 - 267s - loss: 0.1511 - acc: 0.9426 - val_loss: 0.1663 - val_acc: 0.9334

Epoch 00011: val_acc improved from 0.93139 to 0.93342, saving model to
self_cas_study/models/best_model.h5
Epoch 12/20
187/187 - 270s - loss: 0.1426 - acc: 0.9438 - val_loss: 0.2024 - val_acc: 0.9249

Epoch 00012: val_acc did not improve from 0.93342
Epoch 13/20
187/187 - 267s - loss: 0.1403 - acc: 0.9459 - val_loss: 0.2423 - val_acc: 0.9168

Epoch 00013: val_acc did not improve from 0.93342
Epoch 14/20
187/187 - 268s - loss: 0.1374 - acc: 0.9492 - val_loss: 0.1848 - val_acc: 0.9293

Epoch 00014: val_acc did not improve from 0.93342
Epoch 15/20
187/187 - 266s - loss: 0.1354 - acc: 0.9473 - val_loss: 0.1728 - val_acc: 0.9321

Epoch 00015: val_acc did not improve from 0.93342
Epoch 16/20
187/187 - 270s - loss: 0.1368 - acc: 0.9484 - val_loss: 0.1853 - val_acc: 0.9314

Epoch 00016: val_acc did not improve from 0.93342
Epoch 17/20
187/187 - 269s - loss: 0.1422 - acc: 0.9455 - val_loss: 0.1526 - val_acc: 0.9382

Epoch 00017: val_acc improved from 0.93342 to 0.93818, saving model to
self_cas_study/models/best_model.h5
Epoch 18/20
187/187 - 270s - loss: 0.1209 - acc: 0.9517 - val_loss: 0.2423 - val_acc: 0.9205

Epoch 00018: val_acc did not improve from 0.93818
```

```
Epoch 19/20
187/187 - 269s - loss: 0.1293 - acc: 0.9486 - val_loss: 0.1944 - val_acc: 0.9317

Epoch 00019: val_acc did not improve from 0.93818
Epoch 20/20
187/187 - 270s - loss: 0.1309 - acc: 0.9517 - val_loss: 0.1845 - val_acc: 0.9287

Epoch 00020: val_acc did not improve from 0.93818
```

[24]:

```
def plot_hist(hist):
  plt.plot(hist.history["acc"])
  plt.plot(hist.history["val_acc"])
  plt.title("model accuracy")
  plt.ylabel("accuracy")
  plt.xlabel("epoch")
  plt.legend(["train", "validation"], loc="upper left")
  plt.show()
plot_hist(history)
```

[24]:



3 Evaluation

[25]:
```
# Evaluate the model
loss, acc = model.evaluate_generator(validation_generator,validation_steps)
```

```
/opt/conda/lib/python3.7/site-
packages/tensorflow/python/keras/engine/training.py:1877: UserWarning:
`Model.evaluate_generator` is deprecated and will be removed in a future
version. Please use `Model.evaluate`, which supports generators.
  warnings.warn('`Model.evaluate_generator` is deprecated and '
```

[26]:
```
# let's lookinto accuracy and log-loss
print("Restored model, accuracy: {:5.2f}%".format(100 * acc))
print("Restored model, log-loss {}:".format(loss))
```

```
Restored model, accuracy: 93.17%
Restored model, log-loss 0.18241988122463226:
```

[27]:
```
# Let's predict on validation data
true_lables = validation_generator.labels
batch_size = 32
nb_validation_samples = 3000
steps = nb_validation_samples / batch_size
predictions = model.predict_generator(validation_generator, steps,verbose=1)
y_pred = np.array([np.argmax(x) for x in predictions])
```

```
/opt/conda/lib/python3.7/site-
packages/tensorflow/python/keras/engine/training.py:1905: UserWarning:
`Model.predict_generator` is deprecated and will be removed in a future version.
Please use `Model.predict`, which supports generators.
  warnings.warn('`Model.predict_generator` is deprecated and '

93/93 [==============================] - 55s 573ms/step
```

[28]:
```
# creat data frame with ture values and predict values
val_files = validation_generator.filenames
val_compare = pd.DataFrame({"Filename":val_files,"Abnormal":predictions[:
↪,0],"Normal":predictions[:,1],"Ture_lab":true_lables})
```

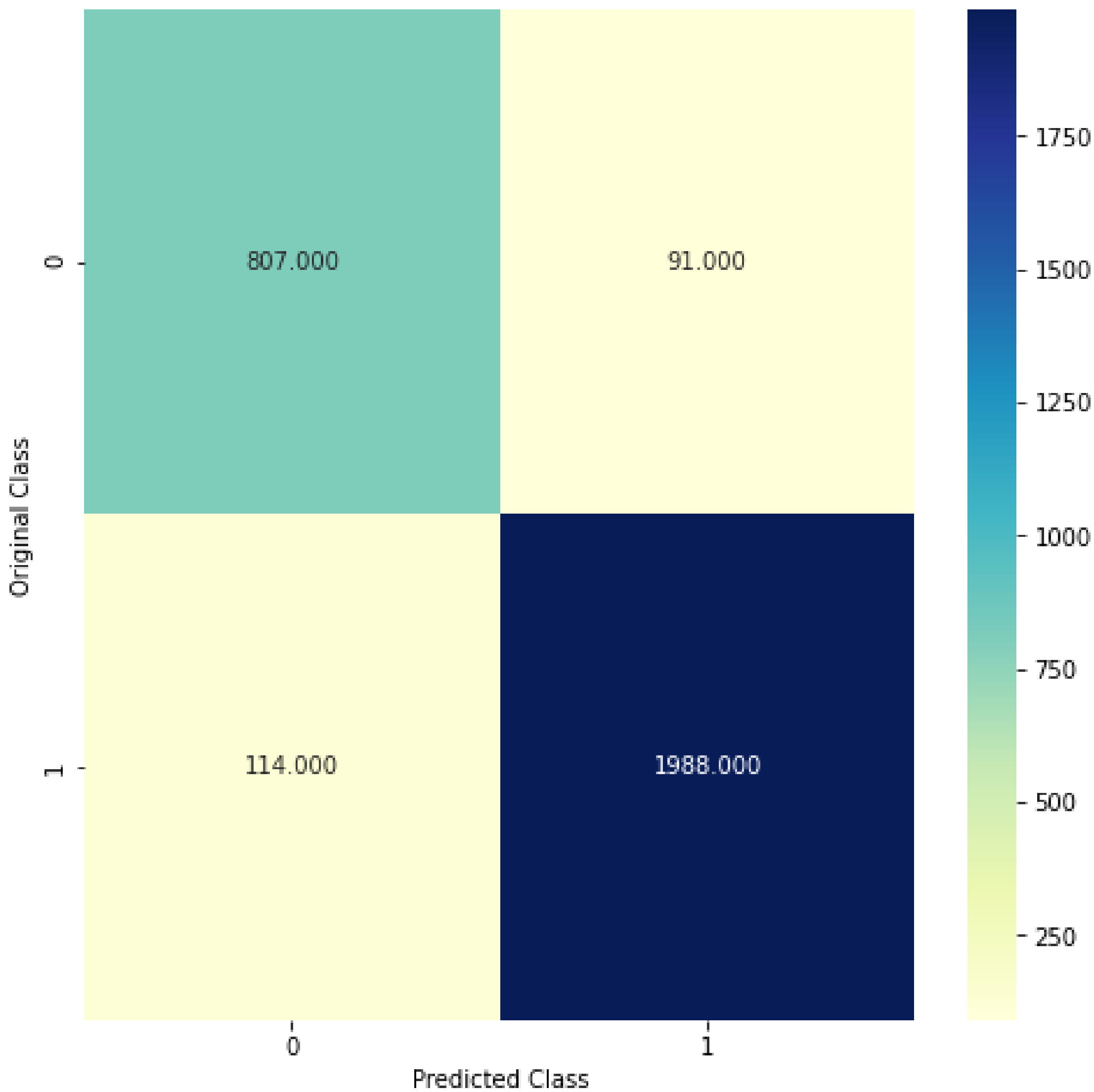
[29]:
```
# lets plot confusion matrix
def plot_confusion_matrix(test_y, predict_y):
  C = confusion_matrix(test_y, predict_y)
  A =(((C.T)/(C.sum(axis=1))).T)
  #divid each element of the confusion matrix with the sum of elements in that␣
↪column
  B =(C/C.sum(axis=0))
  labels = [0,1]
  # representing A in heatmap format
```

```python
    print("-"*20, "Confusion matrix", "-"*20)
    plt.figure(figsize=(8,8))
    sns.heatmap(C, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels,␣
 ↪yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
```

[30]:
```python
plot_confusion_matrix(true_lables, y_pred)
```

```
-------------------- Confusion matrix --------------------
```

[30]:

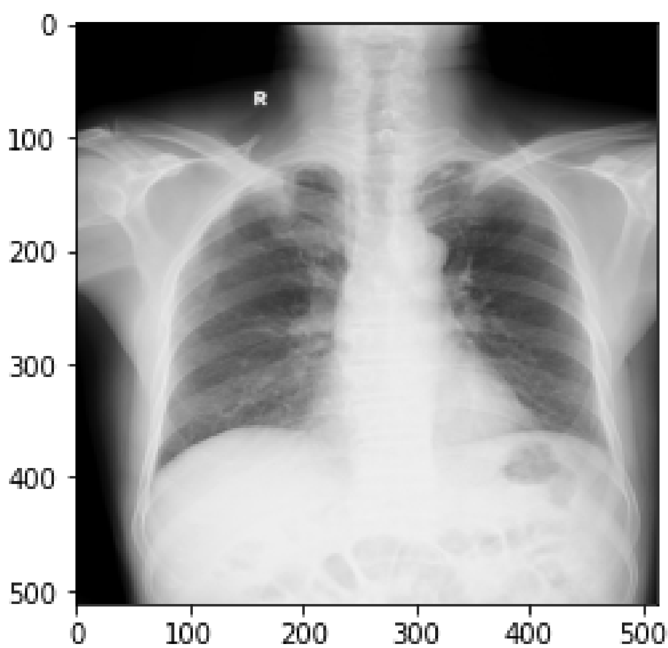


[31]:
```
# Let see visual image how model is performing
def Human_evaluation(img_id):
  dataset_dir = '../input/vinbigdata/train'
  # Define the paths to the training and testing dicom folders respectively
  ture_data = df_train[df_train['image_id'] ==img_id]
  img_path = append_ext(img_id)
  pre_data = val_compare[val_compare['Filename'] == img_path ]
  ture_class = ture_data.class_name.unique().tolist()
  print("Ture image class are {}".format(ture_class))
  print("Probability that a person with Abnormal lung condition: {:5.2f}%".
↪format(pre_data.Abnormal.iloc[0]*100))
  print("Probability that a person with Normal lung condition: {:5.2f}%".
↪format(pre_data.Normal.iloc[0]*100))
  path = os.path.join(dataset_dir,img_path)
  img = mpimg.imread(path)
  plt.imshow(img,cmap="gray")
```

[32]:
```
Human_evaluation("0007d316f756b3fa0baea2ff514ce945")
```

```
Ture image class are ['Pulmonary fibrosis', 'Pleural thickening',
'Cardiomegaly', 'Aortic enlargement', 'ILD']
Probability that a person with Abnormal lung condition: 86.15%
Probability that a person with Normal lung condition: 13.85%
```

[32]:



4 Prediction

[33]:
```
# Load the previously saved weights
model.load_weights('./self_cas_study/models/best_model.h5')
```

[34]:
```
# Let's predict on  test data
filenames = test_generator.filenames
predict = model.predict_generator(test_generator,steps␣
 ↪=len(filenames),verbose=1)
```

```
/opt/conda/lib/python3.7/site-
packages/tensorflow/python/keras/engine/training.py:1905: UserWarning:
`Model.predict_generator` is deprecated and will be removed in a future version.
Please use `Model.predict`, which supports generators.
  warnings.warn('`Model.predict_generator` is deprecated and '
```

```
3000/3000 [==============================] - 50s 16ms/step
```

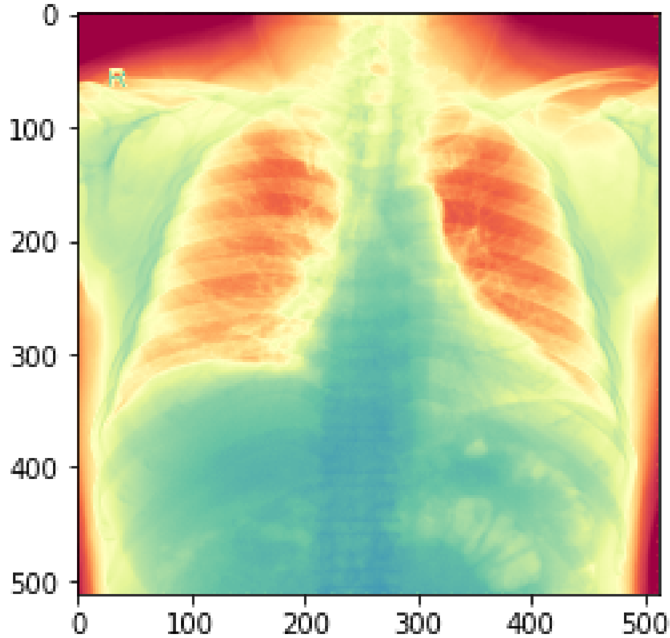
[35]:
```
results=pd.DataFrame({"Filename":filenames,"Abnormal":predict[:,0],"Normal":
 ↪predict[:,1]})
results.to_csv('predection.csv')
```

[36]:
```
# Let's see how model is perfoming on unseen images
def image_prediction(img_id):
  dataset_dir = '../input/vinbigdata/test'
  img_path = append_ext(img_id)
  pre_data = results[results['Filename'] == img_path ]
  print("Probability that a person with Abnormal lung condition: {:5.2f}%".
 ↪format(pre_data.Abnormal.iloc[0]*100))
  print("Probability that a person with Normal lung condition: {:5.2f}%".
 ↪format(pre_data.Normal.iloc[0]*100))
  path = os.path.join(dataset_dir,img_path)
  img = mpimg.imread(path)
  plt.imshow(img,cmap="Spectral")
```

[37]:
```
image_prediction('00a2145de1886cb9eb88869c85d74080')
```

```
Probability that a person with Abnormal lung condition: 99.74%
Probability that a person with Normal lung condition:  0.26%
```

[37]:



R
0
100
200
300
400
500
0
100
200
300
400
500